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GRAND CHALLENGES CENTENNIAL COLLECTION

Subseasonal to Seasonal Prediction of Weather to Climate with Application to Tropical Cyclones

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Key Points:
- Subseasonal to seasonal prediction is a new and rapidly developing area of forecasting capabilities
- Collaborative research on interactions between weather and climate has been accelerated by new multimodel databases of forecasts
- Subseasonal tropical cyclone forecasts have improved substantially with good prospects for developing useful early warning systems

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Abstract Demands are growing rapidly in the operational prediction and applications communities for forecasts that fill the gap between daily weather forecasts and seasonal climate outlooks. Recent scientific advances have identified sources of predictability on this time range, and modeling advances are leading to better forecasts. However, much remains to be done to further improve their skill and to develop new climate service forecast products to help countries and sectorial decision makers better manage weather risks and extremes and to adapt to climate change. This paper reviews the history and describes the main challenges and opportunities for the modeling and forecast-applications communities to improve subseasonal to seasonal (S2S) forecasts and products, along with current developments catalyzed by the World Weather Research Programme and World Climate Research Programme's joint Sub-Seasonal to Seasonal Prediction Project. The case of tropical cyclones is highlighted as an illustrative example of the points discussed.

Plain Language Summary The forecast range between weather forecasts and seasonal outlooks was long thought to be a "predictability desert" with little forecast skill. However, many management decisions in agriculture and food security, water, disaster risk reduction, and health fall into this gap in prediction capabilities, so that developing forecast capabilities for this time range would be of considerable societal value. New research and better models have begun to close this gap through increased international collaboration between weather and climate forecasting centers, national research programs, and the academic and user communities. Better understanding of the coupled ocean-atmosphere-land-cryosphere system has identified multiple sources of S2S predictability that are starting to be exploited to fill the prediction gap spurred by creation of new forecast databases.

1. Introduction

Historically, there has been a clear separation between weather and climate prediction despite the fact that both use a similar numerical approach. Weather prediction refers to the prediction of daily weather patterns up to about 10 days in advance, whereas climate prediction targets time-aggregated weather conditions from weeks to decades in advance. This separation has been accompanied by a divide in the weather and climate research communities, largely for the historical reasons described below. However, a convergence is taking place driven by societal needs for weather and climate forecast information on multiple time scales in the context of a changing climate and by the fact that weather and climate take place on a continuum of time and space scales. Huge advances have been made in weather and climate forecasting since their advent in the mid and late twentieth century, respectively, thanks to revolutions in computers, earth observations, forecast systems, and scientific understanding of the earth system. It is now well established that coherent weather and climate phenomena on a range of time scales along this continuum lead to predictability from subdaily, to weeks, months, years, decades, and beyond (Hoskins, 2012). The grand challenge is to harness this predictability to create skillful and usable forecasts across time scales to inform socioeconomic planning decisions toward a more weather and climate resilient world.

The focus of this paper is on forecast lead times of about 2 weeks to a season ahead, the so-called subseasonal to seasonal (S2S) time scale, in between traditional weather and climate forecasts. We chart the recent development of S2S forecasting from its roots in weather and seasonal climate forecasting, from the multiple sources of S2S predictability, through the S2S ensemble prediction systems, to the nascent S2S forecast products that are now being produced. We highlight TCs as an illustration of how an important weather phenomenon is modulated by S2S sources of predictability and how forecast maps for strike probability are now being made several weeks in advance. International collaboration has been instrumental to invigorating recent work in the field through the Sub-seasonal to Seasonal Prediction Project—also known as simply the "S2S project"—which began in 2014 under the joint auspices of the World Weather Research Programme (WWRP) and World Climate Research Programme (WCRP). The paper emphasizes the role of this coordination, which has enabled developments in S2S prediction to connect operational forecasting centers around the world with modeling and prediction research in academia and beyond, as well as to connect with new developments in climate services for forecast uptake.

Section 2 provides a brief historical introduction to the forecasting of weather, seasonal climate, tropical cyclones, and the ensemble prediction systems used. Section 3 introduces S2S prediction and its current status, with examples from tropical cyclone prediction, together with an introduction to the activities of the international S2S Prediction Project. Section 4 is devoted to current developments, challenges, and opportunities in S2S forecasting, including new activities of the second phase of the S2S project. One of the key reasons for the emergence of S2S is the growing societal need for forecasts for better proactive management of weather and climate risks, which is addressed in Section 5. The article concludes in Section 6 with some thoughts on possible future developments.

2. Weather and Climate Forecasting

2.1. Historical Background

The source of weather predictability is often described in terms of the instantaneous state of the atmosphere together with the governing fluid-dynamical equations. Determinism of weather processes makes predictions possible, while chaos in the presence of initial errors and model deficiencies limits it (Toth & Buizza, 2019). The theoretical deterministic predictability limit of the large-scale midlatitude atmosphere was estimated to be about 2 weeks in the famous work of Lorenz (1963, 1969), with a currently realizable limit of about 10 days (Zhang et al., 2019), corresponding to the typical reach of today's forecasts of midlatitude synoptic-scale daily weather. Sources of weather predictability involve the atmospheric synoptic-scale *phenomena* that dominate local weather and whose dynamics evolve in a potentially predictable way. These include tropical and extratropical cyclones, monsoon depressions, tropical easterly waves, and even mesoscale convective systems (MCSs). The time scales of these phenomena as well as their spatiotemporal distributions play a critical role in determining the extent of weather predictability at a particular location/time of year. For example, the Lorenz 2-week limit applies to midlatitude weather which is dominated by the evolution of baroclinic wave life cycles of about 10 days. Weather forecasts have less skill in the tropics where weather is dominated by MCSs with mostly subdaily lifetimes (Houze, 2004) but can capitalize on tropical wave motions such as African easterly waves, which have a period of about 4 days (Kiladis et al., 2006). Since the lifetimes of atmospheric phenomena generally increase with spatial scale, so does the deterministic predictability limit (Toth & Buizza, 2019). Atmospheric wave phenomena grow and propagate due to fluid-dynamical instabilities (e.g., baroclinic and convective), and while the determinism of these instabilities enables prediction, they also cause errors in the initial state to grow. Errors can also grow due to numerical instabilities, as well as atmospheric phenomena such as sound and gravity waves, underlying the importance of formally stable numerical integration schemes and the filtering of the governing equations to remove these waves (Charney, 1947). The quest for skillful weather forecasts is to maximize the predictable signals associated with coherent atmospheric (or climate) phenomena against the background of error growth from a myriad of sources.

Numerical weather prediction (NWP) had its roots early in the twentieth century when new understanding of atmospheric dynamics led to the development of the primitive equations of the atmosphere (Abbe, 1901; Bjerknes, 1904) and later key simplifications that made their numerical solution for the synoptic scales tractable (Charney, 1947). In tandem with the early development of computers, these theoretical developments led to the first operational weather forecast (i.e., routine predictions for practical use) based on the barotropic equation in 1954 (Harper et al., 2007; Persson, 2005). The huge subsequent improvements in computing capacity, model physics, data assimilation, and the advent of satellite data starting in the 1980s have led to remarkable increases in skill in the range from 3 to 10 days ahead. Skill has increased continuously by about 1 day per decade since the 1980s, resulting in what has been called the "quiet revolution" in NWP (Bauer et al., 2015).

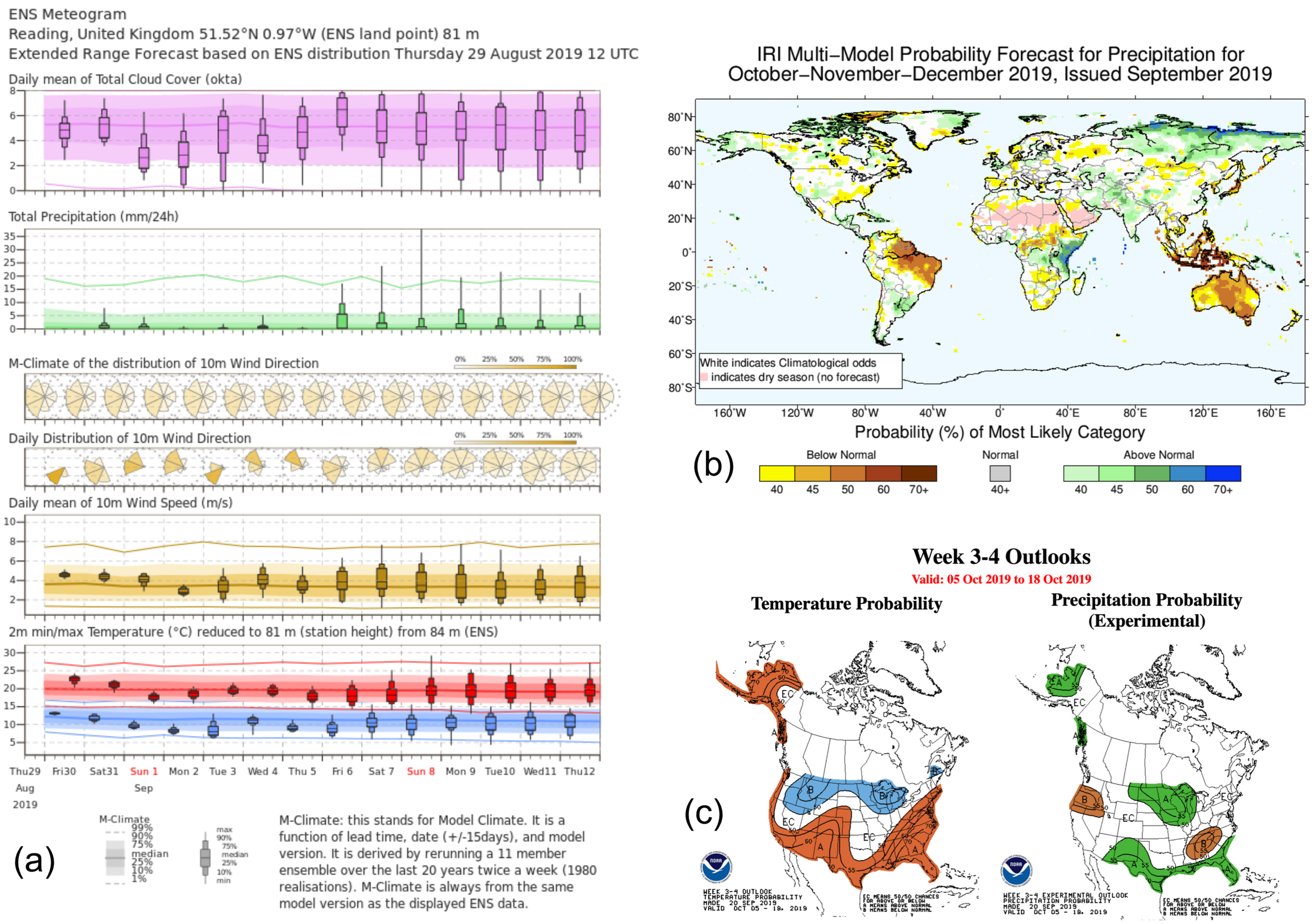

Figure 1. Forecast formats used for weather, seasonal, and subseasonal time ranges. (a) ECMWF Meteogram for Reading, UK, issued 29 August 2019, for each day 29 August to 12 September; (b) IRI multimodel seasonal precipitation probability forecast, issued 15 September 2019, for the October–December 2019 season (https://iri.columbia.edu/our-expertise/climate/forecasts/seasonal-climate-forecasts/); (c) NOAA Climate Prediction Center week 3–4 outlook, issued 20 September for the 5–19 October 2-week period (https://www.cpc.ncep.noaa.gov/products/predictions/WK34/). The probabilities in (b) refer to tercile categories and in (c) to above/below median.

On longer time scales, seasonal climate predictions from dynamical models are now well established (Goddard et al., 2001; Palmer et al., 2004), predicated on slowly evolving earth surface boundary conditions—primarily tropical sea surface temperature (SSTs) but also soil moisture, snow cover, and sea ice—and their impacts on weather characteristics. The El Niño-Southern Oscillation (ENSO) is the dominant source tropical SST seasonal variability and can be predicted many months in advance on average by current models (Barnston et al., 2012). However, ENSO's episodic nature means that the predictable signal and prediction skill vary greatly from year to year. Besides the predictability limits of ENSO itself, seasonal climate forecasts rely on robust impacts of surface boundary conditions on the atmosphere, either locally or remotely through atmospheric teleconnection patterns. These impacts vary greatly by location and season. The episodic nature of ENSO coupled with the spatial (and seasonal) heterogeneity of ENSO impacts on weather implies that skillful seasonal forecasts are only possible at certain times and locations. These locations/times are sometimes called "windows of forecast opportunity," which contrast with the more-uniform skill of weather forecasts (Mariotti et al., 2020). The fluctuations in seasonal climate predictability gave rise to the well-established practice of issuing seasonal forecasts in probabilistic terms, also accounting for the fact that the impact of SST on daily weather statistics is not deterministic. Aggregation of rainfall of temperature over a 3-month season is typically employed to enable predictable signals to predominate over daily weather noise.

2.2. Ensemble Prediction Systems

Dynamical seasonal prediction systems share many similarities with NWP: both use time integration of the fluid dynamical equations and initialization of the forecasts using data assimilation. The main distinctions in seasonal prediction are (a) the use of coupled ocean-atmosphere general circulation models (GCMs), often with interactive sea ice, needed to predict the evolution seasonal climate while NWP models have historically been atmosphere only, using prescribed SSTs, and (b) lower horizontal resolution to enable longer simulations up to 12 months or more in advance. Seasonal forecasting generally includes initialization of the land surface and ocean as well as the atmosphere (e.g., Saha et al., 2014; Stockdale et al., 2018). Data assimilation is usually done separately for each component, introducing inconsistencies, although coupled data assimilation is under development (Penny & Hamill, 2017). Due to its inherently probabilistic nature, it was recognized early on in seasonal forecasting that the ensemble mean could greatly enhance the predictive signal by filtering out the weather-scale noise associated with atmospheric chaos and that an ensemble over multiple models could reduce model error through cancelation of errors between models (Goddard et al., 2001; Hagedorn et al., 2005). This evolution toward ensemble prediction systems has also taken place in NWP, though for somewhat different reasons (e.g., Bauer et al., 2015). NWP forecast skill is more dependent on the best possible estimate of the atmospheric initial conditions, so the perturbed initial conditions around the best guess serve primarily as a mean to estimate the forecast uncertainty. Most NWP models also now use stochastic physics to take into account model errors (e.g., Charron et al., 2010), and this approach is becoming more common in climate models as well (Berner, 2017; Weisheimer et al., 2014). In NWP, there is a strong relationship between the skill and the spread of the forecast ensemble, so the latter can be used directly to estimate forecast uncertainty (Scherrer et al., 2004). The spread-skill relationship is less pronounced in seasonal forecasting of precipitation because much of the uncertainty is due to unpredictable atmospheric dynamics, rather than inaccurate initial conditions; here, the ensemble mean provides a better estimate of the predictable part, while the uncertainty is sometimes derived from hindcast error statistics (Tippett et al., 2007).

Currently, 11 operational forecast centers around the world routinely produce global NWP medium-range weather forecasts every 6 to 12 hours, up to 1–2 weeks ahead at horizontal resolutions which range from 16 km to about 200 km. These weather forecasts have been archived since 2007 in the TIGGE database, designed to provide operational ensemble forecast data to the international research community (Swinbank et al., 2015). The original name of TIGGE, "THORPEX Interactive Grand Global Ensemble," reflected the World Weather Research Programme (WWRP)'s The Observing System Research and Predictability Experiment (THORPEX) vision to develop a global interactive forecast system that would be configured interactively in response to varying weather situations and user needs (Bougeault et al., 2010). An analogous infrastructure exists for seasonal forecasts, also known as long-range forecasts (predictions valid for a period of longer than 30 days). There are currently 13 global producing centers (GPCs) of long-range forecasts designated by the World Meteorological Organization (WMO), together with a WMO Lead Centre that issues multimodel ensemble forecast graphical products (https://www.wmolc.org). While the raw numerical real-time forecast output is not generally accessible, the hindcast data are available under open access through the Climate-System Historical Forecast Project (Tompkins et al., 2017). Besides the WMO framework, seasonal forecasts from North American modeling centers have been made publicly accessible every month in real time through the North American Multimodel Ensemble (NMME) database (Kirtman & Co-authors, 2014). A similar initiative has recently begun in Europe under the Copernicus Climate Change Service (C3S), enabling real-time access European GPCs (http://climate.copernicus.eu/seasonal-forecasts). Besides pivotal access to the seasonal forecasts in real time, both NMME and C3S contain hindcast sets for each ensemble prediction system, which are used for forecast skill assessment as well as to develop statistical forecast calibrations; both are essential components of creating seasonal forecast products suitable for applications.

Examples of weather and seasonal climate forecast operational products are shown in Figure 1, highlighting the different character of weather versus climate forecast information issued. Weather forecasts are specific to each day and location for multiple weather quantities, while seasonal forecasts are categorical, typically issued as probability maps for the favored category of precipitation and temperature, or for probabilities of exceeding a user-chosen threshold (Barnston & Tippett, 2014). While weather forecasts typically convey uncertainty using confidence intervals derived directly from forecast ensembles (Figure 1a), seasonal forecasts highlight the difference between the statistically calibrated forecast and climatological distributions in a course-grained way, such as using just tercile categories (below-normal, near-normal, and above-normal) (Figure 1b). Figure 1c shows an example of a subseasonal week 3–4 outlook for 2-week averages of precipitation and temperature, which is formatted in a similar way to a seasonal forecast, here in terms of the probability of above (green) or below (brown) median.

2.3. Tropical Cyclone Forecasting on Daily and Seasonal Scales

Tropical cyclones (TCs) are highly coherent large-scale storms with typical lifetimes of 7 days. An average of 90 tropical cyclones occur across the tropical basins each year. They provide a window of S2S forecast opportunity when they occur. The first attempts to make weather forecasts of Atlantic hurricanes occurred in Cuba in the late nineteenth century by Jesuit priests. Based on the information on weather stations across the Caribbean and their knowledge of hurricanes, they projected the storms' paths. By the early twentieth century, weather services of countries affected by hurricanes were attempting to forecast hurricane trajectories based on the existing observations and give early warnings to their citizens. During World War II, the United States started regular aircraft reconnaissance in typhoons. The data from these flights and radars made it possible to improve the monitoring and forecasting of tropical cyclones (Emanuel, 2018). In the 1960s, statistical forecasts of hurricane tracks with some skill were developed using large-scale environmental predictors from numerical weather models. There has been significant improvement in the skill of hurricane forecasts since then, in particular, in hurricane tracks, while hurricane intensity remains a challenge (Zhang & Emanuel, 2018). Current hurricane intensity forecasts for individual storms are still far from their predictability limit (Emanuel & Zhang, 2016). The reasons for this discrepancy are well known, ranging from incomplete understanding of boundary layer and air-sea interaction at high-wind speeds, to issues in assimilating observations correctly in the models (Emanuel, 2018; Emanuel & Zhang, 2016). Currently, most agencies issue 5-day operational weather predictions of individual storms. Although many forecast agencies predict genesis with lead times up to 5 days or less, they only forecast the subsequent track and intensity after genesis has occurred (Sobel & Pillai, 2018). Track forecasts are intrinsically dependent on the forecast of steering winds. In cases when these winds have poor predictability, for example, the recent Hurricane Dorian, track forecasts will have more uncertainty as well. The National Hurricane Center expresses the uncertainty of these tracks as a cone of uncertainty based on past track forecast errors (https://www.nhc.noaa.gov/aboutcone.shtml). Users are known to routinely misinterpret the meaning of the cone of uncertainty (Broad et al., 2007).

The first seasonal tropical cyclone (TC) forecasts were made in the early 1980s by Neville Nicholls for the Australian basin (Nicholls, 1979) and William Gray for the North Atlantic (Gray, 1984a, 1984b). These first statistical forecasts were based on the relationship between tropical cyclone activity in these regions and ENSO. Statistical seasonal tropical cyclone forecasts have changed and improved significantly during the last 30 years, in particular, with the development of globally gridded reanalysis products (Klotzbach, Saunders, et al., 2017; Klotzbach, Chan, et al., 2017). During this period, different techniques have been applied to develop tropical cyclone seasonal forecasts, for instance, dynamical seasonal forecasts, where TC-like storms are tracked in GCMs (Camargo & Barnston, 2009; Chen & Lin, 2011; Vitart et al., 2007), as well as statistical-dynamical techniques (Vecchi et al., 2011; Zhang et al., 2016). The number of groups issuing operational seasonal TC forecasts has boomed in the last decade as well, from 11 across the globe in 2007 (Camargo, Barnston, et al., 2007a) to more than 20 today in the North Atlantic basin alone (Caron et al., 2019). These are typically basin-wide forecasts for specific diagnostics of tropical cyclone activity, such as number of TCs, hurricanes, hurricane days, and accumulated cyclone energy. Unfortunately, there is no uniformity in the variables predicted in these forecasts, or their format, with some deterministic (with an error bar) and some probabilistic forecasts (typically terciles) (Klotzbach et al., 2019). The physical basis for these forecasts is the changes in the environment associated with the variability of various climate modes, in particular ENSO (e.g., Camargo et al., 2010).

3. Sub-Seasonal to Seasonal (S2S) Prediction

The S2S time scale is defined here to mean forecasts beyond 2 weeks but less than a season ahead. This is often referred to as the “gap” between weather and climate, being both too long for much memory of the atmospheric initial conditions to persist and too short for anomalies in surface boundary conditions to be felt sufficiently strongly. The gap also reflects the previous dearth in operational forecast availability between the medium range (up to 14 days) and seasonal forecasts (an average over the next 3 months). Attempts were made at several operational centers in the 1980s and 1990s to fill this gap, but there was scant evidence at the time that these forecasts were skillful, giving rise to the notion that the S2S time scale was a "predictability desert."

What changed since then? Vitart and Robertson (2019) identified four factors leading to the renewed interest in S2S prediction: (1) the discovery of sources of subseasonal to seasonal predictability associated with atmosphere, ocean, and land processes; (2) improvements in medium-range weather forecasting skill; (3) development of seamless prediction; and (4) demand from users for S2S forecasts.

As in weather and seasonal forecasting, identifying the weather/climate processes and phenomena with predictability on weekly to monthly scales has been key. Unlike in the former cases where atmospheric synoptic-scale phenomena such as tropical/extratropical cyclones and ENSO dominate, respectively, the S2S scale potentially contains the impacts of many more sources of predictability, associated with interactions between tropospheric wave dynamics with more-slowly evolving components of the earth system, including the stratosphere, land surface, upper ocean, and the cryosphere (cf. Figure 1 of Mariotti et al., 2019). This is a developing field of research, but the most important S2S predictability sources identified to date are as follows:

- The Madden-Julian Oscillation (MJO): as the dominant mode of intraseasonal variability of organized tropical convective activity, with a period of 30–60 days, the MJO has a considerable impact not only in the tropics, but also in the middle and high latitudes, and is considered as a major source of global predictability on the subseasonal time scale (Zhang, 2013); dynamical models have shown remarkable improvements in MJO forecast skill scores in recent years (Vitart, 2017).
- Soil moisture: memory in soil moisture can last several weeks and influence the atmosphere through changes in evaporation and surface energy budget, affecting subseasonal forecasts of air temperature and precipitation over certain regions during certain seasons (e.g., Koster et al., 2010).
- Snow cover: The radiative and thermal properties of widespread snow cover anomalies have the potential to modulate local and remote climate over monthly to seasonal time scales (e.g., Lin & Wu, 2011; Sobolowski et al., 2010).
- Stratosphere-troposphere interaction: signals of changes in the polar vortex and the Northern Annular Mode/Arctic Oscillation (NAM/AO) are often seen to propagate downward from the stratosphere, with the anomalous tropospheric flow lasting up to about 2 months (Baldwin et al., 2003; Domeisen et al., 2019). Stratosphere-troposphere coupling in the Southern Hemisphere polar vortex is also an important dynamical process that provides predictability of the tropospheric Southern Annular Mode (SAM) and its associated surface impacts (Byrne & Shepherd, 2018; Kuroda & Kodera, 1998; Lim et al., 2019; Thompson et al., 2005).
- Ocean conditions: anomalies in SST lead to changes in air-sea heat flux and convection which affect atmospheric circulation. Forecasts of tropical intraseasonal variability are found to be improved when a coupled atmosphere-ocean model is used (e.g., Woolnough et al., 2007), and ENSO can still makes an important contribution on subseasonal scales (Li & Robertson, 2015). Extratropical SSTs, particularly in the westerly boundary currents, also represent an important source of S2S predictability (Saravanan & Chang, 2019).

The potential for skillful S2S forecast had to await better MJO simulation and prediction, improved coupled atmosphere/ocean/land/cryosphere models and better model horizontal and stratospheric resolution. The seamless predictability paradigm across multiple weather-climate time scales has become increasingly prevalent over the last decade, as witnessed by a sequence of recent publications (Brunet et al., 2010; Hoskins, 2012; Hurrell et al., 2009; Shapiro et al., 2010). Can the theoretical 2-week limit of Lorenz be broken? First, as already mentioned, the Lorenz limit was derived in the context of midlatitude atmospheric dynamics of baroclinic waves, which have life cycles of about a week. The key to predictability on subseasonal time scales is the existence of predictable phenomena on those time scales, such as the MJO. The second aspect is that time averaging on the relevant scale is critical; while the details of the weather on a specific day will not be predictable beyond 1–2 weeks, weekly or longer aggregates of weather statistics may be predictable in many cases (in the probabilistic sense of climate forecasts). What should the averaging period be for S2S forecasts? Zhu et al. (2014) have suggested that the averaging period should increase in tandem with the lead time, with a 1-week averaging corresponding a to a 1-week lead time, and so on.

3.1. International Collaboration on S2S Prediction

In 2013, the WCRP joined forces with the WWRP to launch the S2S Prediction Project (S2S) with the goal of improving forecast skill and understanding in the gap between weather forecasts and seasonal climate predictions, from 2 weeks to a season ahead (Vitart et al., 2012). Special emphasis was put on high-impact weather events, developing coordination among operational centers via WMO's Commission for Basic Systems, and on promoting uptake of S2S information by the applications communities, such as through the WMO's Global Framework for Climate Services (GFCS) (e.g., Vaughan & Dessai, 2014). In WWRP, the S2S project became one of three post-THORPEX activities along with the Polar Prediction Project (Jung et al., 2016) and the High Impact Weather project (Zhang et al., 2019). The 11 operational centers routinely producing subseasonal forecasts play a key role in S2S, while its WCRP and WWRP foundations engage the research communities, facilitating research-operations two-way interactions.

Motivated by the success of the TIGGE data archive of weather forecasts, a major initial thrust of the S2S project was to create a similar database for subseasonal forecasts, to facilitate intercomparison of models, assessment of forecast skill, and analysis of S2S predictability mechanisms. The S2S database (Vitart et al., 2016), launched in 2015, contains 11 models, many of which stem from NWP models, with a few from seasonal forecasting, with horizontal and vertical resolutions that are in general intermediate between them. Currently, eight are coupled ocean-atmosphere models, and this number has been increasing; all eight now include active sea ice. The frequency of initializing forecasts varies; some models are run in burst mode on a subweekly basis with a large ensemble size (e.g., ECMWF, BoM, and ECCC), whereas other models are run in continuous mode on a daily basis with a smaller ensemble size (e.g., NCEP, UKMO, KMA) (Buizza, 2019; Vitart et al., 2016). The database contains subseasonal forecasts 3 weeks behind real time as well as hindcasts/reforecasts; it is officially hosted at ECMWF and the China Meteorological Administration (CMA), with the majority of the data subsequently archived in IRI, Columbia University. The database has enabled major research activity on S2S predictability, modeling, forecast verification, and product development, with over over 1,200 users from over 90 counties and 75 articles published by September 2019 (see http://s2sprediction.net).

The WMO Lead Centre for Long Range Forecasting and Multimodel ensembles (LC-LRFMME) began a pilot real-time subseasonal MME prediction system for its members in 2015, taking advantage of the S2S database at ECMWF, but without the 3-week delay placed on public access. Through the increased S2S international coordination, all 11 operational centers in S2S now issue their forecasts on Thursdays (including the four models with daily forecast starts), compared with only seven in 2013, facilitating multimodel ensemble forecasts (e.g., Vigaud, Robertson, & Tippett, 2017).

The renewed interest in S2S forecasting led to the development of the Subseasonal Experiment (SubX) project in the United States, which has created an additional multimodel database of subseasonal forecasts and reforecasts from seven North American models (Pegion et al., 2019). While similar in form to the S2S database and also archived in the IRI Data Library, SubX differs from S2S in several respects. Importantly, SubX forecast is accessible in near real time in order to provide subseasonal prediction guidance to NOAA, without the 3-week delay imposed by S2S. SubX also includes research models alongside operational models from NOAA and Environment and Climate Change Canada, facilitating feedback between research and operations on model development.

3.2. Subseasonal Forecasting of Tropical Cyclones

Similarly to other types of forecasts, there is a clear gap at subseasonal scales between weather forecasts of individual tropical cyclones several days ahead and the seasonal forecasts which focus on TC activity statistics months in advance. In the last few years, there has been a large focus of the scientific community on the understanding and prediction of tropical cyclones on these intermediate subseasonal time scales (e.g., Camargo et al., 2019). The modulation of tropical cyclones at subseasonal times scales was first noted in the Chinese literature (Li et al., 2018; Xie et al., 1963). Although not recognized at the time, they were describing the modulation of typhoon occurrence by the MJO, subsequently discovered by Madden and Julian (1972). Both Nakazawa (1986) and Liebmann et al. (1994) later documented an increase of TC activity when the MJO was active over the western North Pacific and North Indian regions. Following these pioneering studies, the modulation of TCs by the MJO was identified in other regions, namely, the eastern North Pacific (Maloney & Hartmann, 2000a; Molinari et al., 1997), the Gulf of Mexico (Aiyyer & Molinari, 2008; Maloney & Hartmann, 2000b), the Atlantic main development region (Klotzbach, 2010; Mo, 2000), South

Indian Ocean (Bessafi & Wheeler, 2006; Ho et al., 2006), Australian region (Hall et al., 2001), and southwest Pacific (Chand & Walsh, 2009). More recently, Klotzbach (2014), Klotzbach and Oliver (2015) analyzed the MJO-TC relationship globally. Furthermore, Camargo et al. (2009) showed that a genesis index (Camargo, Emanuel, & Sobel, 2007b) could reproduce the modulation of the TC activity by the MJO in the environment (see Figure 2). Once MJO convection is active in a specific region, the environmental conditions become more conducive to genesis and there is a tendency to have an increase in tropical cyclogenesis in that region during or just following the active MJO phase.

Besides the MJO, various other modes of variability are known to impact TC activity on subseasonal time scales. For instance, Ventrice et al. (2012) and Schreck (2015) showed that convectively coupled Kelvin waves inhibit TC genesis a few days prior to the arrival of the convective phase at a certain location, while TC genesis is enhanced after its passage. The anomalies associated with the Kelvin wave persist longer than the Kelvin wave itself, as they are usually embedded within the leading edge of the MJO convective phase. Extratropical-tropical interaction can also modulate TC activity on subseasonal time scales through Rossby wave breaking episodes, in particular, in the North Atlantic (e.g., Wang et al., 2018).

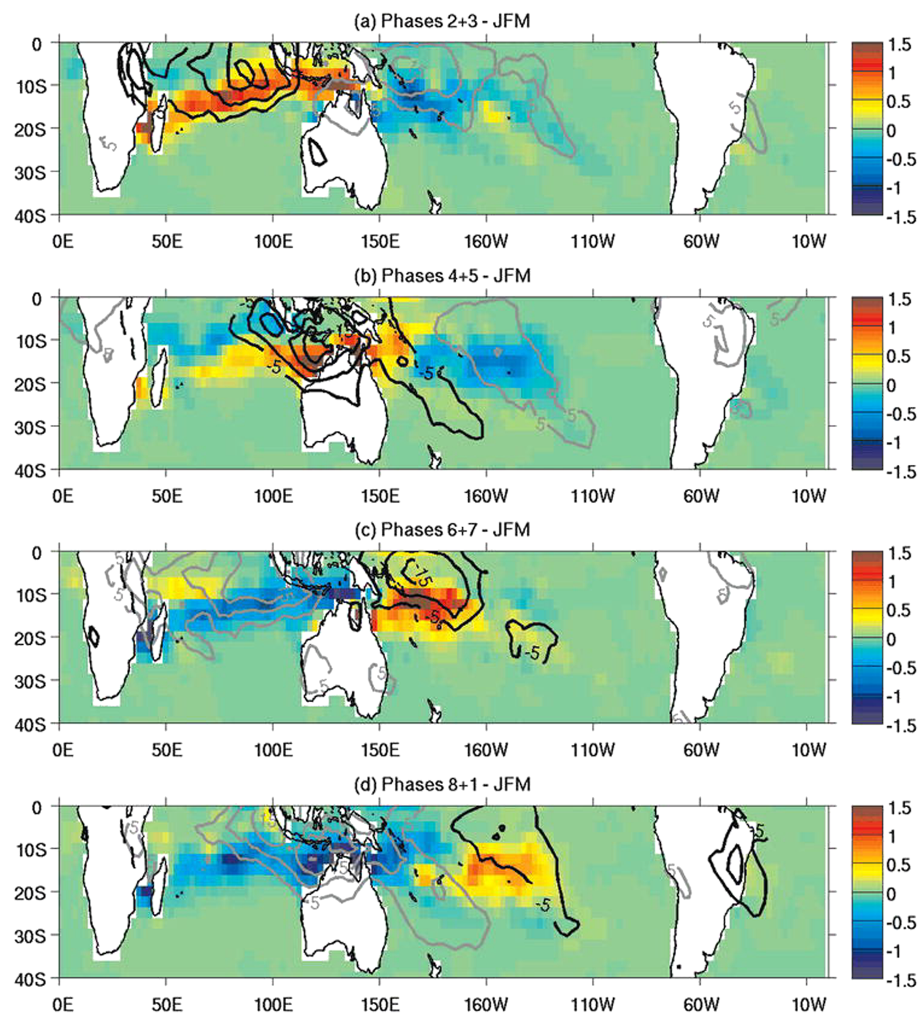

Figure 2. Genesis Potential Index (GPI; colors) and Outgoing Longwave Radiation (OLR; contours) anomaly composites for January to March (JFM) in different MJO phases. The OLR positive (negative) anomalies are shown in gray (black) and the contours are plotted for every 5 W m^{-2} for MJO phases (a) 2 and 3 (Indian Ocean), (b) 4 and 5 (Maritime Continent), (c) 6 and 7 (western Pacific), and (d) 8 and 1 (Western Hemisphere and Africa). The GPI was calculated using the NCEP-NCAR reanalysis data for the period 1982–2007. Figure originally from Camargo et al. (2009), which describes datasets used. ©American Meteorological Society. Used with permission.

As in the case of TC seasonal forecasts, the first subseasonal forecasts of TC activity were statistical (Leroy & Wheeler, 2008), based on logistic regression of TC days with MJO and Indo-Pacific SST indices, given that the dynamical models were not able to simulate well or forecast the MJO (Ahn et al., 2017; Kim et al., 2009). As the simulations the MJO in dynamical models improved they were able to reproduce the observed modulation of TCs (Vitart, 2009), as shown in Figure 3, which led to the development of the TCs subseasonal forecasts with skill similar to the statistical ones (Vitart et al., 2010). Slade and Maloney (2013) used a similar method as Leroy and Wheeler for the Atlantic and east Pacific basins. Examples of typical weather, subseasonal, and seasonal tropical cyclone forecast products from ECMWF are given in Figure 4. On weather time scales, the forecasts focus on the intensity and tracks of individual storms. In contrast, at longer time scales, the forecasts give information on probability of TC occurrence, as well as integrated quantities, such as ACE (accumulated cyclone energy), which includes information of TC counts, intensity, and duration.

Many studies have focused on the predictability of specific TCs in forecasting systems. For instance, Xiang et al. (2015) examined the predictability of the GFDL system for Hurricane Sandy and Super Typhoon Haiyan and found that their genesis could be predicted with 11 days lead time, while their landfall locations could be predicted 1 and 2 weeks ahead of time, respectively. In contrast, other studies analyzed the skill in a specific season and basin. Elsberry et al. (2010, 2011) examined the ability of the ECMWF system in forecasting typhoons in 2008 and 2009 at lead times of 5–30 days ahead.

However, in order to have a more complete understanding of the real ability of current systems in forecasting TC activity on subseasonal time scales, it is fundamental to analyze retrospective forecasts of many models over many years. The S2S dataset is exactly what is needed to do that type of analysis. Yamaguchi et al. (2016) examined ability of four system of the S2S database in predicting western North Pacific TCs over 4 weeks. More recently, Lee et al. (2018) evaluated the S2S database subseasonal probability of basin-wide

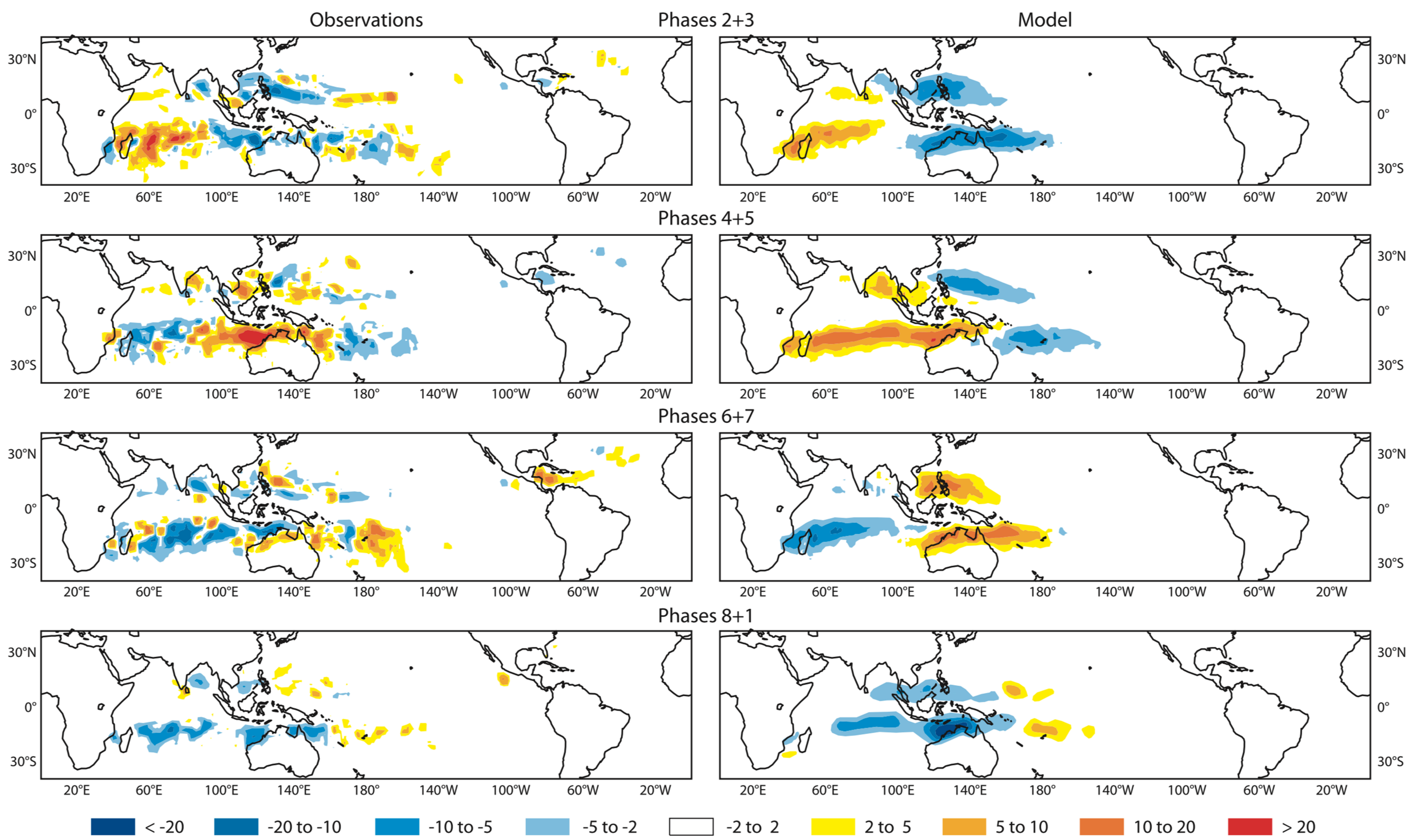

Figure 3. Tropical storm density anomalies (×1000) as a function of MJO phases in (left) observations and in the (right) model hindcasts for the period November to April 1989 to 2008. The anomalies are computed relative the 1989–2008 climatology. Yellow and red colors indicate an increase of tropical cyclone activity. The blue colors indicate a reduction of tropical cyclone activity. Figure originally from Vitart (2009), which describes datasets used. ©American Geophysical Union. Used with permission.

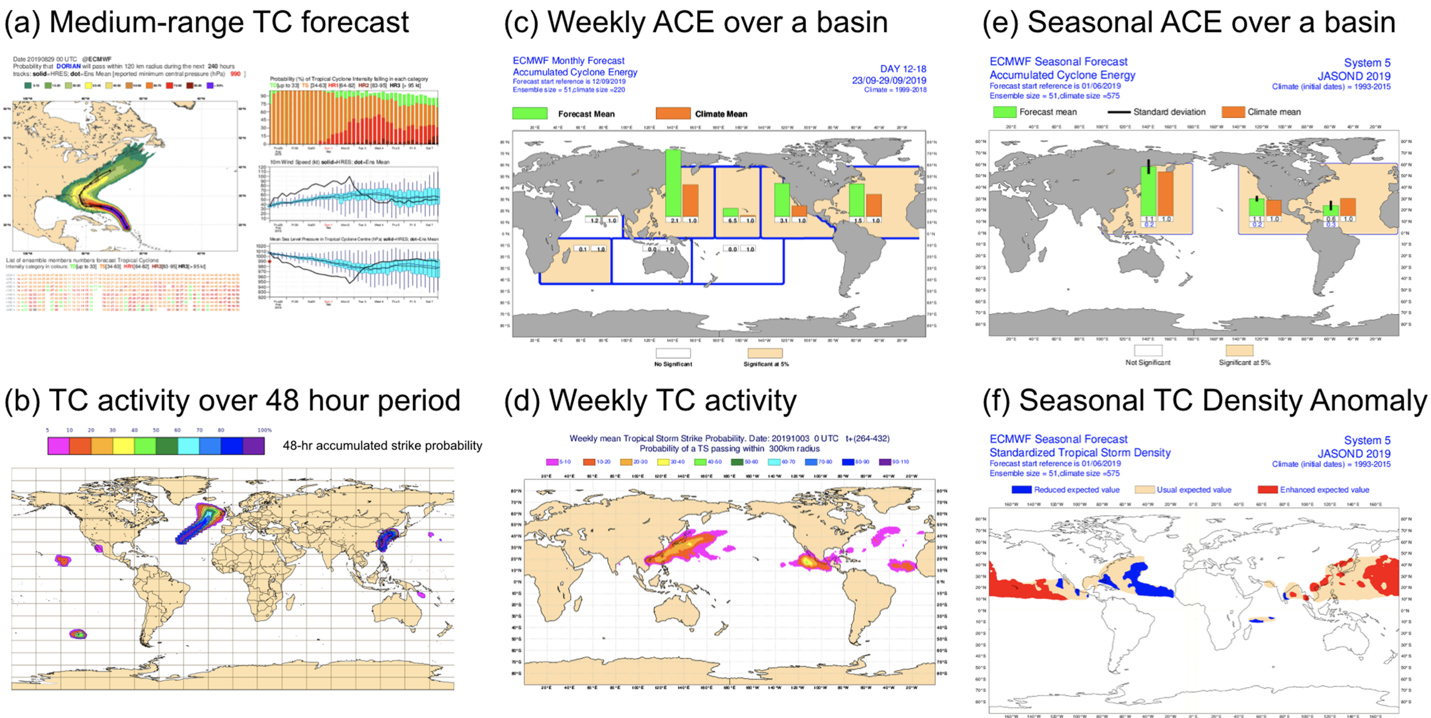

Figure 4. ECMWF tropical cyclone products on weather and subseasonal and seasonal time scales. (a) Tropical cyclone strike probability over the next 10 days associated to a tropical cyclone present in the initial conditions. (b) Tropical cyclone strike probabilities over a 48 hour period from tropical cyclones present in the initial conditions as well as from tropical cyclone genesis produced by the model. (c) Accumulated cyclone energy predicted by the ECMWF extended-range forecasts over a weekly period over each ocean basin (green bars are model forecasts and orange bars represent the climatology). (d) Probability of tropical cyclone strike over a weekly period. (e) Accumulated cyclone energy predicted by the ECMWF seasonal forecasting system SEAS5 over a season (green bars) compared to climatology (orange bars). (f) Tropical cyclone density anomalies over a season.

TC occurrence on weekly time scales using the Brier Skill Score. While most models have more skill than climatology for week 1, the skill decreased sharply after that. Model initialization was clearly important in determining the skill across the S2S multimodel ensemble. Furthermore, since TC activity is related to MJO phase in S2S models (Lee et al. 2018, and Figure 3 for an earlier version of the ECMWF model), ongoing advances in MJO prediction skill can be expected to translate into even better TC forecasts in the near future.

Currently, only a few centers issue operational subseasonal TC forecasts. The only publicly available forecast is from Colorado State University (CSU) for the North Atlantic. This statistical-dynamical probabilistic forecast for 2-week North Atlantic Accumulated Cyclone Energy (ACE) in terciles is issued for the North Atlantic during the peak hurricane season (August to November) and shows positive skill above persistence from the prior 2 weeks. The other operational subseasonal TC forecasts are not public, namely, ECMWF, BoM, and CMA. The first two are dynamical, while the CMA is statistical-dynamical. The ECMWF issues week 1–4 forecasts in all TC-prone regions. These forecasts have been issued since 2010 and consist of various products, such as the weekly values of the number of tropical storms and hurricanes, and ACE over a TC basin, as well as a TC strike probability anomaly maps of TC passing within 300 km of a location. The forecasts are issued twice a week. These forecasts can be superior to statistical techniques if suitably calibrated (Vitart et al., 2010) and are more skillful than weekly observed climatology and persistence for weeks 1 and 2 (all basins) and beyond week 3 in a few TC basins. The Australian BoM started producing subseasonal forecasts for the southern hemisphere TC season in the 2017–2018 season. These forecasts have performance similar to ECMWF and provided useful guidance in two major cyclones in the southern hemisphere (Cyclones Gita and Hilda) (Gregory et al., 2019). Camp et al. (2018) also showed that the BoM system manages to predict modulation of TC tracks by the MJO phase with a lead time of 5 weeks.

Figure 5 shows the ECMWF forecast of TC strike probability over the tropical NW Pacific for the week of 2–8 December 2019, when the Philippines was hit by Typhoon Kammuri (known locally over the Philippines as Typhoon Tisoy). Panel (a) shows the forecast issued on 2 December which corresponds to week 1 of the forecast, with that issued on 11 November (week 4) shown in panel (b). The strike probabilities are

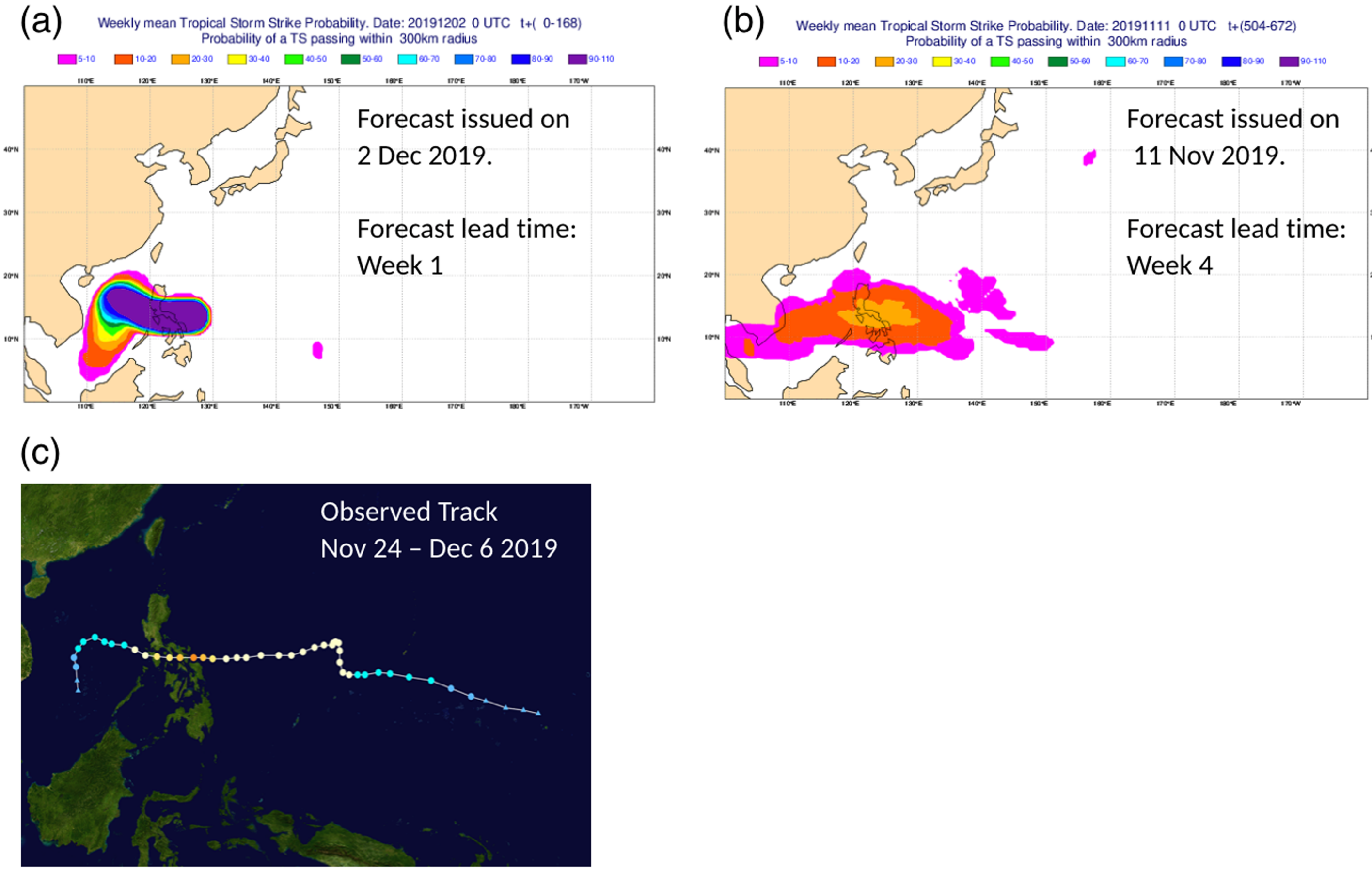

Figure 5. ECMWF TC strike probability forecasts for the week of 2–8 December 2019, initialized on (a) 2 December (week 1) and (b) 11 November (week 4). Strike probability is defined as the probability of a tropical storm passing within a 300 km radius of a gridpoint. The climatological strike probability over the Philippines in December is about 5%. (c) The observed track of Typhoon Kammuri, 24 November to 6 December 2019.

calculated from the spread of the 51 forecast ensemble members, providing users with an estimate of forecast confidence. The week 1 forecast is highly confident with strike probabilities exceeding 90% over the central Philippines, which correspond well with the observed track of Kammuri (panel c). The week 4 forecast from 11 November also predicted elevated strike probabilities of 20–30% over the central Philippines. While the forecast confidence is reduced, the area of elevated probabilities corresponds quite well to the short lead forecast, illustrating the growing the potential for valuable TC forecasts in the subseasonal range.

4. Challenges and Opportunities

4.1. Gap Analysis

Much of the research, product development, and uptake by the applications communities are still at quite early stages, and a lot still needs to be done to realize the vision of skillful S2S forecasts of societal value. To inform the second phase of the international S2S project that began in 2019, a questionnaire was circulated in 2018 to the research, modeling, and operational communities for feedback (WMO, 2018). Frequently mentioned gaps included the following: land-surface processes and initialization; ensemble generation, including initialization, perturbation methods, and stochastic physics; coupled data assimilation and the role of the ocean and sea ice on the subseasonal forecasts; stratospheric processes; and understanding model systematic errors and error growth. Some of the database and operational gaps raised include the following: need for more convenient and faster access to popular suites of variables, including ensemble means, model climatologies, indices, and map displays; need for multimodel calibrated forecast product development; desire for more extensive reforecast sets (number of years and ensemble members) for verification and forecast calibration and encouraging centers to harmonize reforecasts; request for more ocean data including 3D fields and increased model horizontal and temporal resolution; and desire for real-time access.

For the applications/service/donors/wider stakeholder audience, a set of semistructured interviews was carried out by the WWRP's Working Group on Societal and Economic Research Applications (SERA).

The interviewees generally agreed that while the potential benefits of skilful S2S forecasts are high, several barriers hinder their realization, namely:

- Lack of accuracy/poor skill: high level of accuracy is required for many types of decision making.
- Lack of post-processing: need for statistical post-processing techniques to calibrate forecast for reliable probabilities.
- Lack of forecast verification: request that forecasts always be provided with verification information.
- Lack of stability in forecast model output: instability/persistence of the rainfall in the forecasts prevented the use of the forecast, or they became reliable only close to the actual event.
- Challenges in interpretation of probabilities: a large share of users struggle to interpret probabilities and can have low expertise in risk management.

4.2. Some Current Developments

Current estimates of probabilistic week 3–4 precipitation skill over land are fairly comparable to those of seasonal forecasts, as illustrated in Figure 6, derived from seasonal NMME and subseasonal SubX multimodel ensemble (MME) system hindcasts, respectively. The subseasonal Rank Probability Skill Score (RPSS; Weigel et al., 2007) (panel b) exhibits few large negative values, indicating that the hindcasts are well calibrated, as in the seasonal case (panel a). For the December starts shown, regions of positive week 3–4 RPSS values occur in some of the same regions as for the seasonal forecasts (e.g., northern South America, the Philippines), while positive subseasonal skill often appears more widespread than for the seasonal case, such as over eastern Africa and the Arabian peninsula (Vigaud et al., 2018). The construction of well-calibrated MME systems for S2S remains much more difficult than for seasonal forecasts due to the lack of adequate hindcasts and a forecast/hindcast protocol that is common across the different S2S models. Long hindcast sets with an adequate number of ensemble members and with the same hindcast start dates across models are required to train and evaluate forecast calibration methods and easily average across multiple models for common target periods (Coelho et al., 2018). This is still far from the case for the operational S2S models where computational infrastructure constraints generally prioritize model spatial resolution at the expense of shorter hindcast sets with fewer ensemble members. Identifying suitable compromises and trade-offs in forecast system design is a challenge under practical constraints for operational activities (costs, priorities, and timeliness) and demands further research (Takaya, 2019). A step forward was taken by SubX which strove toward a common protocol, but where hindcast ensembles were still often compromised in terms of ensemble size (Pegion et al., 2019).

There is evidence that multimodel ensembles provide increased skill over individual models on subseasonal scales (Strazzo et al., 2019; Vigaud, Robertson, & Tippett, 2017; Vigaud, Robertson, Tippett, Acharya, 2017), as is well established in seasonal forecasting, so that better S2S hindcast protocols that enable better calibration and bias correction can be expected to improve skill. Research is required to revisit the trade-off between spatial resolution and ensemble size at the subseasonal range. However, it may be that the overall predictability in S2S range is fundamentally less, on average, than on the seasonal scale, due to the differing signal-to-noise ratios discussed above. Nonetheless, useful subseasonal forecasts may still be possible if the episodic nature of sources of predictability could be exploited, providing so-called forecasts or windows of opportunity when they occur (Mariotti et al., 2020). The skill in Figure 6b may be much higher if only large-amplitude MJO events are considered, for example. Or skill may be higher for certain classes of extreme events, enabling urgently needed better early warning system forecast products.

Besides improving the forecast products based on better hindcasting sets, many ideas have been put forward toward improving the model forecasts themselves, through model improvements and better initialization, many of which were discussed at the International Conferences on Subseasonal to Decadal Prediction, held in Boulder, CO, in September 2018 (Merryfield et al., 2019). Most current operational systems are initializing each model component separately. Coupled data assimilation of the atmosphere-ocean-land-cryosphere system (Penny & Hamill, 2017) is an area of active development that is likely to bring more consistent S2S forecast initialization in the near future; for example, there are large variations in initialized sea ice fields between current S2S models (Zampieri et al., 2018). Land surface initialization is a recognized weakness in S2S models because land data assimilation is still at a relatively early stage of development, observational limitations exist despite the increased use of satellite remote sensing of soil moisture, and the

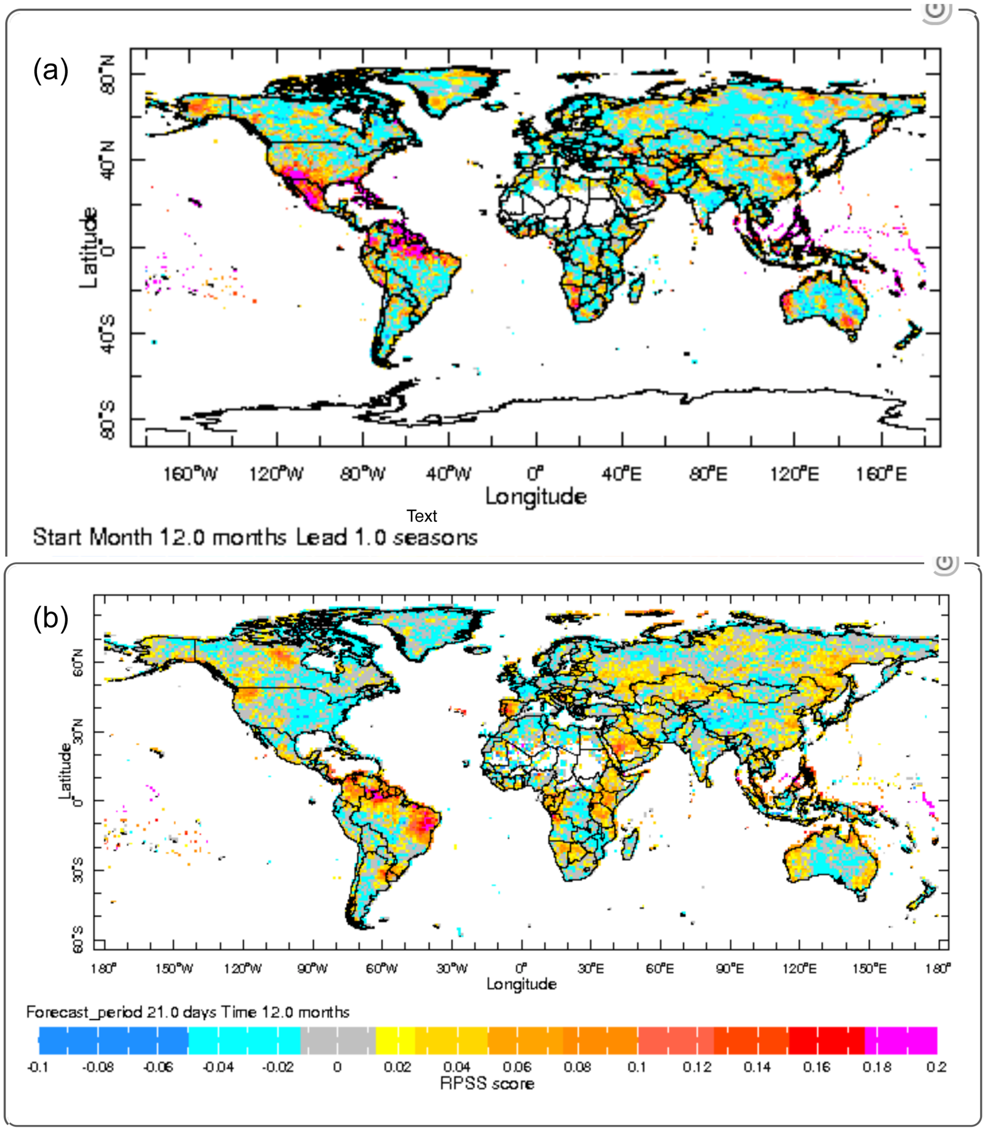

Figure 6. Precipitation probabilistic hindcast skill of (a) seasonal and (b) experimental subseasonal forecasts, expressed using the Rank Probability Skill Score (RPSS). (a) Seasonal Jan-Mar precipitation from hindcasts initialized in December by the IRI system https://iri.columbia.edu/our-expertise/climate/forecasts/seasonal-climate-forecasts/ (b) week 3-4 precipitation from a three-model SubX MME, for hindcasts initialized in December using the methodology of (Vigaud, Robertson, & Tippett, 2017). Reproduced from the IRI global seasonal and subseasonal forecast maprooms: http://iridl.ldeo.columbia.edu/maproom/Global/. The NMME and S2S datasets used were obtained via IRI Data Library.

fact that historically land surface and atmospheric models are developed separately, and their coupled behavior is not calibrated or validated (Dirmeyer et al., 2019). Subseasonal forecasts of the MJO are often underdispersive, requiring better methods to represent the uncertainty in initial conditions (bred vector, singular vector, ensemble data assimilation, and lagged ensembles) and through model stochastic physics (Leutbecher, 2017).

Models continue to exhibit serious systematic errors, ranging from dry biases that inhibit MJO propagation around the Maritime Continent in boreal winter (Kim, 2017) and poor MJO midlatitude teleconnections (Vitart, 2017). While these may often be removed through post-processing (given adequate hindcasts), their feedbacks onto the S2S dynamics cannot, and a major challenge is to improve the models. The stratosphere is now recognized as important for the Northern Hemisphere as well as for the Southern Hemisphere, in both modulating MJO predictability by QBO phase and as a pathway for tropical-extratropical teleconnections and a source of S2S predictability through polar stratosphere-troposphere interactions including sudden stratospheric warmings. This requires models with higher vertical resolution, lid height, adequate small-scale wave parameterizations, and orographic and non-orographic gravity wave drag, as well as stratospheric ozone chemistry which may provide some source of predictability on S2S time scales. New generations of prediction systems have rapidly improved in many of these areas but much remains to be done (Butler & Coauthors, 2019; Tripathi & Coauthors, 2015).

4.3. Tropical Cyclones

Although considerable progress has been made in the last few years in seasonal and subseasonal TC forecasts, there are still many challenges ahead (Camargo et al., 2019). While there is some skill in these forecasts, the skill is highly dependent on the system, the basin, and whether there was extratropical influence or not. It is extremely hard to compare the skill across studies, as there is no standard definition for these forecasts. While some studies consider a system to be skillful if it forecasts correctly the probability of TCs in a basin (total activity), others require skill of the anomaly deviations from the basin seasonal climatology. Furthermore, each system uses very different outputs in their forecasts, ranging from a specific number of events in a basin, to a local probabilities in specific areas. On top of that, different studies use different lead times, periods, and skill scores. This lack of uniformity is a huge problem for potential stakeholders. One important step toward improving the usability of these forecasts would be to have common standards and verification metrics for subseasonal TC forecasts. With improvements in the MJO forecasts and propagation, as well as other modes of variability, TC subseasonal forecast skill can be expected to increase in the near future.

4.4. International S2S Project Developments

As outlined in the previous sections including the S2S the gap analysis, it was recognized that much more work is needed to improve the models and ensemble prediction systems and that further steps are needed to deliver S2S forecast products suitable for operational and applications use. Thus, a three-pronged strategy was developed to (1) continue and enhance the success of the S2S database, (2) form new science subprojects, and (3) give more emphasis on research-operations two-way transfer and on demonstrating new forecast applications. Work is continuing to maintain and enhance the current S2S database at ECMWF, CMA, and IRI. Ocean variables are being added to the S2S database, as per the original plan, and more surface variables four times a day (instead of only once a day), such as 10 m wind needed for energy applications, will be considered. Additional models are planned, such as the extended-range forecasts from the Indian Meteorological Department and NASA. The potential to leverage the many scientific and modeling working groups of the WCRP and WWRP is fundamental to success of the S2S project, which in turn provides an integrating mechanism for the activities coordinated by those programs. The WCRP is developing a new implementation plan for the coming decade (2019–2028) with increased emphasis on initialized climate prediction from weeks to decades and on linking climate science with society (WCRP, 2019). Six new S2S research subprojects have been designed to exploit these linkages:

- MJO prediction and teleconnections in collaboration with the Working Group for Numerical Experimentation (WGNE) MJO Task Force with focus on MJO/high-impact weather relationships and tropical-extratropical interactions;
- Land initialization and configuration, in coordination with the Global Energy and Water Exchange/Global Land Atmosphere System Study (GEWEX/GLASS), Data Assimilation and Observing Systems (DAOS), EartH2Observe, and Working Group for Sub-Seasonal to Interdecadal Prediction (WGSIP) SNOWGLACE project, to investigate the fidelity of model representations of land-atmosphere interactions, and how S2S forecasts may be improved by taking better advantage of the information contained in land surface states;
- Ocean and sea ice initialization and configuration in coordination with WGSIP, DAOS, and PDEF (Predictability, Dynamics, Ensemble Forecasting) Working Groups to promote improved subseasonal predictions though improved initialization of the ocean-sea ice state and depiction of key ocean and sea ice processes that provide predictability at subseasonal time scales;
- The stratosphere, in collaboration with the WCRP Stratosphere-troposphere Processes And their Role in Climate (SPARC) initiative on Stratospheric Network for the Assessment of Predictability (SNAP), with focus on quantification and understanding of stratosphere/troposphere coupling, model biases, initial conditions and ensemble generation, and whole atmosphere diagnostics;

- Atmospheric composition, in collaboration with WGNE and Global Atmospheric Watch (GAW) to assess the benefits of using prognostic aerosols rather than the climatology used in the current operational S2S models, identify the level of aerosol model complexity needed, and assess the predictability of aerosols (e.g. dust) at the S2S time scale and potential forecast value for applications;
- Ensemble generation, in collaboration with PDEF and WGNE, to determine (on the S2S scale) the optimal initial-perturbation strategies on S2S scale, sources of overconfident forecasts, importance of initial perturbations of the ocean, and stochastic parameterization schemes.

The operational global producing centers have been the backbone of S2S, and the transition of S2S research to operations (R2O) will be fundamental to realizing its full potential by developing/testing methodologies for calibration, multimodel combination, verification, and generation of forecast products, and in coordination with the relevant WMO technical commissions to define the standards and protocols for operational implementation and exchange of S2S forecasts. The goal is to transition the data-exchange infrastructure that supports research into the operational domain by the end of the S2S Prediction Project in 2023.

5. Societal Implications

Promoting the uptake of S2S forecasts to help inform socioeconomic decision making is a complex and multifaceted, yet critical, task if S2S forecasts are to be of value to society. The decision-making situations that S2S forecasts can inform are various, but some examples include civil protection or humanitarian aid agencies preparing for a high-impact weather event (Bazo et al., 2019), or improved agricultural production, reservoir management (Robertson et al., 2014), or public health outcomes (Tompkins et al., 2019). Research on the potential use of S2S forecasts for applications has started only recently, and S2S-based early warning systems, fully integrated with decision support, have yet to emerge. Many challenges remain, including the need to create better skill estimates and user-friendly forecast products and to communicate them effectively (Robbins et al., 2019).

More collaboration between forecast developers and potential stakeholders will be critical in order to develop user-relevant forecast quantities and products for S2S forecasts. For example, IRI seasonal forecasts are issued as probabilities of exceedance that enable appropriate actions based on user-specific thresholds (Barnston & Tippett, 2014) and help minimize the danger of acting in vain. These are more amenable to early-warning/early-action disaster preparedness strategies, being developed by the Red Cross/Red Crescent Societies, by defining probabilities that trigger action once they exceed a given value for a critical magnitude of drought, for example (Bazo et al., 2019; de Perez et al., 2015). Alternative actions may be better informed as shifts in a continuous set of possibilities, rather than all-or-nothing decisions. Building on well-established experience in seasonal forecast applications (Terra & Baethgen, 2019), successful incorporation of S2S forecasts into actual decisions will require strong and sustained interaction between S2S forecast developers and stakeholders in a co-production process within which trust can be established (Robbins et al., 2019). In the health sector, partnership platforms created through the Global Framework for Climate Services (GFCS) and related mechanisms could enable the academic and operational communities in climate and health to work together on real-time health early warning systems, especially in developing countries where climate-driven health outcomes can be severe (Tompkins et al., 2019). In the case of TCs, skillful subseasonal forecasts on regional scales could allow more time for better preparedness ahead of landfalling storms.

To accelerate the use of S2S forecasts (which are delayed 3 weeks behind real time in the S2S database), the S2S project has organized a Real-time Pilot Initiative to make the S2S data available as close as possible to real time for a 2-year period (2019–2021) to a limited number of user groups. The initiative aims to develop best-practice guidance on ways to make S2S forecast information useful and truly usable, through projects with an end-user focus. Sixteen participating projects have been identified across a diverse set of sectors (Humanitarian, Agriculture, Forestry and Fishing, Energy, Water, Health, and Disaster Risk Reduction) and with wide geographical coverage (North and South America, Asia, Africa, Europe, and Oceania).

6. Concluding Remarks

The fields of initialized dynamical prediction of weather and climate each have a long history of development resulting in powerful forecasting tools that have become a part of everyday life in the case of weather, while seasonal forecasts are routinely used in many socioeconomic sectors. Forecasts are becoming more important than ever as global warming exacerbates extreme weather risks, including more-intense tropical cyclones. Accelerated by the pressing needs for early warning across multiple time scales, we are witnessing a drive toward seamless prediction that integrates across weather and climate time scales and from forecasters and model developers to end users (WMO, 2015).

S2S forecasts have improved significantly over the past decade. A central goal of the second phase of the S2S project is to provide a pathway for further improvements through research to address some of the following questions:

- What is the benefit of having more complex earth system models for S2S prediction (atmospheric composition, land, and ocean processes)?
- What is the impact of higher horizontal or vertical resolution of the atmosphere or ocean on S2S prediction? The use of convective permitting models (Judt, 2018; Prein et al., 2017) for S2S prediction appears very promising. For example, Weber and Mass (2019) found the propagation of the MJO was better predicted in CPM simulations, which also had more skillful prediction of week 3 extratropical circulation anomalies.
- Is there a need for more observations to improve S2S forecasts? This pertains to both improving daily-resolved datasets in data-sparse regions such as Africa (Dinku et al., 2014; Funk et al., 2015), needed for the calibration and verification of forecasts, as well as to the testing the potential impact of proposed new observing systems for data assimilation for forecast initialization (e.g., Boukabara et al., 2016).
- What is the benefit of multimodel ensembles for S2S prediction and how can we improve multimodel calibration and combination using emerging machine learning techniques (e.g., McGovern et al., 2019)?

S2S provides an example of the greatly increased needs for interdisciplinary scientific research, international cooperation, and close collaboration between the developers and users of forecasts, in order to realize forecast guidance that will be of true value in creating weather and climate resilient societies. Effective S2S climate services will require much more resources in all the areas highlighted in this review, from basic to applied science to society (National Academies of Sciences, Engineering, Medicine, 2016). This immense challenge is reflected in the four objectives in WCRP's 2019–2028 strategic plan: Fundamental understanding of the climate system, Prediction of the near-term evolution of the climate system, Long-term response of the climate system, and Bridging climate science and society (WCRP, 2019). S2S forecasting is a young and rapidly evolving field at the forefront of these new developments. Previously regarded as a predictability desert, significant advances in understanding and models have ushered in the prospect of filling the gap between medium range weather forecasts and seasonal forecasts, providing a critical piece of the seamless forecast hierarchy from days to decades in advance.

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